The Imbalance-Induced Resistive Heating Profiles Analysis for Low Voltage Transformers

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***Abstract*— Phase imbalance in the UK and European low voltage (415V, LV) distribution networks is a widely acknowledged issue. For LV transformers (11 kV/0.415 kV), phase imbalance causes extra energy losses on transformer windings. These extra energy losses induce the imbalance-induced resistive heating, which then causes the increase of LV transformers' winding temperature. A key barrier for understanding the general picture of imbalance-induced resistance heating is the absence of LV transformers' time series loading data, i.e. UK has 900,000 LV transformer, but most of them are not monitored. To address this challenge, a data-driven approach is proposed. It finds representative clusters of the imbalance-induced resistive heating profiles, leverage the data from only 800 LV transformers. Through an extensive case study, the representative imbalance-induced resistive heating profiles are given by cumulative density functions. The case study also reveals that up to 50% resistive heating is produced by the imbalance-induced resistive heating.**

***Index Terms*— resistive heating, phase imbalance, low voltage, transformer operation, three-phase power**

I. Introduction

IMBALANCE-induced resistive heating (extra resistive heating caused by imbalanced three-phase power) accounts for up to 50% of the resistive heating (resistive heating produced by imbalance three-phase power) for low voltage transformers (11 kV/0.415 kV) [1]. It is caused by significant phase imbalance in the UK' and European low voltage networks (415V, LV) [2], [3], [4], [5]. According to the data from [1], the phase imbalance degree is around 50% for half of the LV networks from Western Power Distribution(WPD, one of the UK's distribution network operator), i.e. the heaviest phase current is approximately twice of the lightest phase current. This phase imbalance causes extra winding losses for LV transformers, which then increase resistive heating. Therefore, for identify the efficiency and risks of LV transfomers, the imbalance-induced resistive heating should be considered [6].

There exist a number of references that focus on imbalance-induced resistive heating. Reference [7] calculate the yearly extra energy losses for transformers with the phase imbalance Reference [8] using industrial samples to represent the energy losses of transformers with the phase imbalance. Reference [9] calculates the imbalance caused energy loss on distribution cores based on IEEE-34 test model. The energy losses calculated by the above references are then used to calculate the imbalance-induced resistive heating.

The above references all require LV networks or transformers to be fully monitored, i.e. time-series data (data-recorded every 15 minutes or similar resolutions) or load curve are available in these approaches. However, for most of the 900,000 LV networks in the UK, the monitoring devices are normally absent. Thus, for obtaining a general picture of the imbalance-induced resistive heating profiles, the current approaches are not applicable.

For addressing this gap, a data-driven approach is given to make an original contribution. It leverages minor imbalance-induced resistive heating profiles to build the general picture of the imbalance-induced resistive heating profiles in the UK. To do this, k-means clustering is proposed in this research. Compare to other traditional clustering methods (Gaussian mixture model and hierarchical clustering), k-means clustering gives the least Davies–Bouldin index (an evaluation index for evaluating clustering results).

This research gives an economical way for distribution network operators (DNOs) to identify the representative imbalance-induced resistive heating profiles in the UK, comparing to deploy 900,000 monitoring devices (approximately two billion British Pounds). It, therefore, enables the DNOs to analyze the influence of phase imbalance on transformers operation, e.g. efficiency reduction, temperature rise and especially the risk of overload.

The rest of this paper is organized as follows: Section II presents the data description and the clustering methodology. Section III presents case studies. Section IV concludes this paper.

II. Methodology

To identify the typical profiles of imbalance-induced resistive heating, time-series phase current data from 800 LV transformers are leveraged. These transformers are very representative, i.e. these transformers cover a good mixture of geometry scenarios (urban, suburban and rural areas) and customer scenarios (domestic, commercial, and industrial) [1]. Then, k-means clustering is used to partition these 800 data into meaningful clusters. The cluster number in this process is determined by Davies–Bouldin index. Finally, the typical profiles are proposed as the average value of the data for each cluster. The overall flowchart of the data-driven approach is demonstrated in Fig. 1.

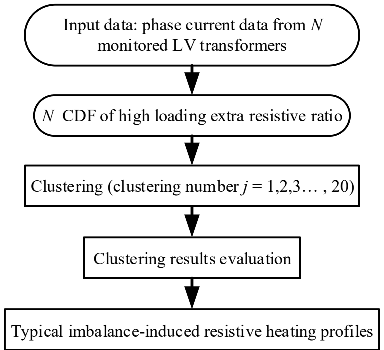

Fig. 1 Overview flowchart

A. Data pre-processing

In this case, 800 LV transformers' yearly time-series phase current data (data are recorded every 15 minutes, given by the project "Low Voltage Network Templates" [1]) are collected within Western Power Distribution's (WPD, a UK DNO) business area. They cover a good mixture of LV network's geographic scenarios (urban, suburban, and rural) and LV network's load scenarios (domestic, commercial, and industrial). For example, the city center of Newport is chosen as an urban area with commercial customers; Lower Machen is selected as a rural area with domestic customers. The details of these data are described in reference [1].

With the time-series phase current, actual winding energy losses $P_{wl}(t)$ and balanced winding energy losses $P_{bl}(t)$ are given by:

$$P_{wl}(t) = (I_a^2(t) + I_b^2(t) + I_b^2(t)) \cdot R \tag{1}$$

$$P_{bl}(t) = 3\left(\frac{I_a(t) + I_b(t) + I_c(t)}{3}\right)^2 \cdot R \tag{2}$$

where $I_a(t), I_b(t), I_c(t)$ denote the currents on phase a, b, and c at time t, respectively; R denotes the transformer winding resistance.

The extra winding loss (extra resistive heating), caused by phase imbalance, is given by:

$$P_{el}(t) = P_{wl}(t) - P_{bl}(t) \tag{3}$$

The corresponding original extra resistive heating ratio r_{oeh} is given by:

$$r_{oeh}(t) = P_{el}(t)/P_{wl}(t) \tag{4}$$

With the imbalance-induced resistive heating and the extra resistive heating ratio calculated for 800 LV transformers, this paper suggests leveraging only the highest 85% loading scenarios to present the imbalance-induced resistive heating profiles. It is because high loading contributes to more influence on transformer operations than low loading scenarios. For example, the transformer has high loading scenario (200A, 300A, 250A) and low loading scenario (50A, 10A, 15A). The extra resistive heating ratio is 2.6% and 33.7% for high loading and low loading scenarios respectively. However, even the low loading scenario gives much higher extra resistive heating ratio, the actual resistive heating is only 19% of the extra resistive heating for high loading scenario. Therefore, it is appropriate for using the highest 85% loading scenarios to present the imbalance-induced resistive heating profiles. Otherwise, to highlight the influence of the extra resistive heating, i.e. the percentage given by the extra resistive heating (caused by phase imbalance) to the actual resistive heating, the extra resistive heating ratio is considered to draw the imbalance-induced resistive heating profile. Given the previous two methods, the original extra resistive heating ratio vectors r_{oeh} shrinks to the high loading extra resistive heating ratio vectors r_{heh} corresponding to the highest 85% loading scenarios.

To draw the imbalance-induced resistive heating profiles, the cumulative density function is considered in this research. It is appropriate because that the aim of finding the typical imbalance-induced resistive heating profiles is to help DNOs to identify the influence of phase imbalance on transformer operation e.g. efficiency reduction, temperature increase, and risk of overload.

For calculating the cumulative density function, kernel density estimation with the lower limit, given by (5) and (6), is leveraged.

$$\mathbf{y} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} \boldsymbol{K}\left(\frac{\boldsymbol{r_{heh}} - \boldsymbol{r_{heh}(i)}}{\boldsymbol{h}}\right) \tag{5}$$

$$f(r_{heh}) = \begin{cases} \frac{1}{n \cdot h}\sum_{i=1}^{n} K\left(\frac{r_{heh} - r_{heh}(i)}{h}\right) & y > 0 \\ 0 & y < 0 \end{cases} \tag{6}$$

where r_{heh} is the high loading extra resistive heating ratio; $r_{heh}(i)$ is the high loading extra resistive heating ratio for i_{th} number in r_{heh}; n denotes the sample size; h denotes the kernel bandwidth. In this paper, the kernel function K is chosen to be the Gaussian kernel [10], given by:

$$K\left(\frac{r_{heh} - r_{heh}(t)}{h}\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{r_{heh} - r_{heh}(t)}{h}\right)^2} \tag{7}$$

where the bandwidth [11] is given by:

$$h = 1.06 \cdot \sigma \cdot n^{-\frac{1}{5}} \tag{8}$$

where σ denotes the standard deviation of the high loading extra resistive heating ratio vector; n denotes the size of each high loading extra resistive heating ratio vector.

For 800 fully monitored LV transformers, the imbalance-induced resistive heating profiles are presented by the cumulative density function of the high loading extra resistive heating ratio.

B. Clustering

In this stage, 800 fully monitored LV transformers are partitioned into several meaningful clusters by 800 CDFs. k-means and agglomerative hierarchical clustering [12] (widely used classical clustering methods) are considered in this research. To choose the appropriate cluster number and method, Davies–Bouldin index is used to evaluate the clustering results. Through an extensive case study, k-means clustering presents lower Davies–Bouldin index (described in Section III-B), i.e. better clustering results are given by k-means clustering. Thus, k-means clustering is selected in this research. In addition, The

Euclidean distance [13] is used in this paper to measure the similarities. The use of Euclidean distance is because it is a widely used method to measure the distance between two points in space.

1) *k-means clustering*

In the first stage, the input matrix for k-means clustering is given by:

$$[f_1, f_2, \cdots, f_{800}]^{\mathrm{T}} \tag{9}$$

where $f_1 \dots f_{800}$ denote the CDF data vector for 800 fully monitored LV transformers;

With the previous input matrix, the k-means clustering is proposed. For k-means clustering, it aims to find j groups ($n = \{n_1, n_2 \dots n_j\}$) of clusters with the least distances among the clusters' center to the observations within these clusters [13], it is solved by a optimization process (given by (9)).

$$\underset{n}{\arg min} \sum_{i=1}^{j} \sum_{x \epsilon n_i} \|x - C_i\|^2 \tag{10}$$

where C_i is the center of the cluster n_i; x is a CDF of high loading extra resistive heating within the cluster n_i.

2) *Determine the clustering number*

To determine the clustering number, an appropriate clustering evaluation method, Davies–Bouldin index, is proposed. This index implies the ratio of the internal distance within two clusters to the external distance between the centroids of the two clusters. The Davies–Bouldin index (DB) is given by:

$$\begin{gathered} DB = \frac{1}{j} \sum_{i=1}^{j} \max\{\frac{S_i + S_q}{M_{i,q}}\} \\ 0 < q < j \\ q \neq i \\ \text{q is an integer} \end{gathered} \tag{11}$$

where S_i is the average internal distance of the i_{th} cluster; $M_{i,q}$ denotes the external distance between the centroids of the i_{th} cluster and q_{th} cluster ; the details of this index is described in reference [14].

According to [14], the least Davies–Bouldin index gives the appropriate clustering number.

With the proposed methods, this research finds the typical imbalance-induced resistive heating profiles from limited data, i.e. using only time-series phase currents from 800 LV transformer to reflect the typical imbalance-induced resistive heating profiles for more than 900,000 LV transformers in the UK.

III. Case Study

This section gives the numerical results. The data processing is talked in Section III-A. The clustering number determination and clustering result is given in Section III-B. The Section III-C gives the discussion.

A. *Data-processing*

Based on Section II-A, the cumulative density function of the high loading (85% of the maximum annual loading) for 800 monitored LV transformers is calculated. Given this results, over 40% of the 800 transformers has 15%-50% of the imbalance-induced resistive heating, i.e. for over 40% of the transformers, if the three phases are balanced when these transformers are heavy loading, there is a maximum reduction of 15%-50% of the resistive heating generation. This is described in Fig. 2.

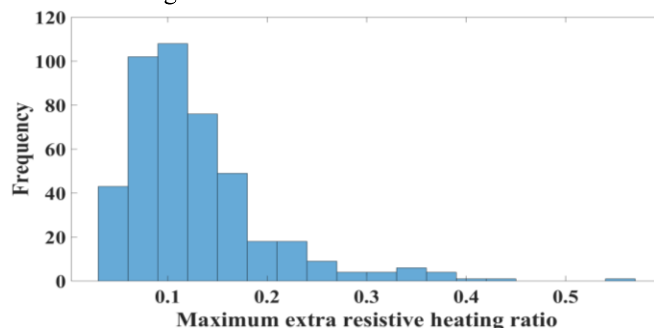

Fig. 2 The histogram of the maximum extra resistive heating ratio for LV transformers

B. *Clustering*

In the first step, the clustering number is determined by Davies–Bouldin index (given in Section II-B, DB). The DB index, given by k-means and agglomerative hierarchical clustering methods, are presented in Fig. 3.

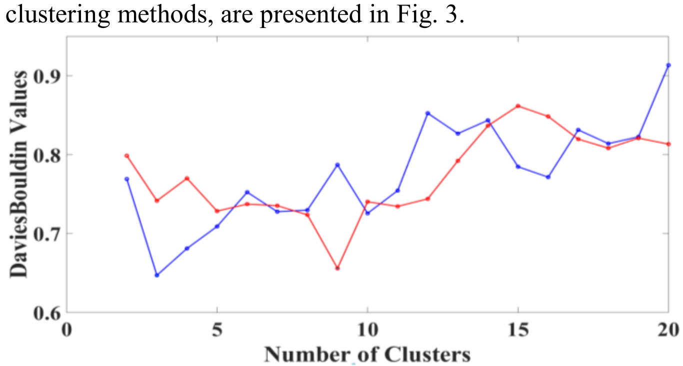

Fig. 3 The Davies–Bouldin index values by k-means clustering (blue line) and agglomerative hierarchical clustering (red line)

In Fig. 3, k-means clustering gives lower Davies–Bouldin index than agglomerative hierarchical clustering. The number of clusters for k-means clustering, given by the least Davies–Bouldin index, is 3. Thus, the clustering number is 3 in this research.

Given the determined number of clusters (j = 3), the 800 CDF are partitioned into 3 groups. The clustering results are plotted in Fig. 4, Fig. 5 and Fig. 6.

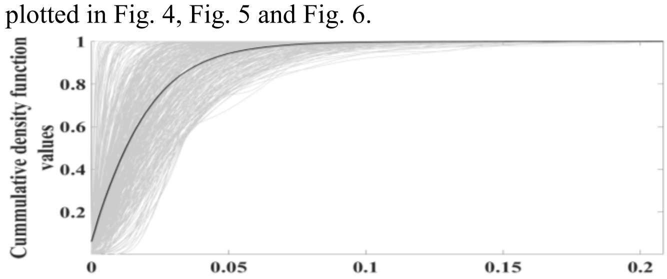

Fig. 4 The imbalance-induced resistive heating profile for cluster 1

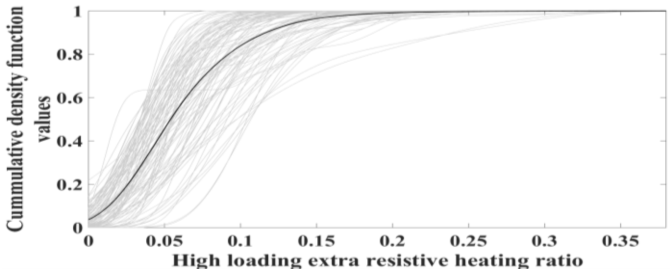

Fig. 5 The imbalance-induced resistive heating profile for cluster 2

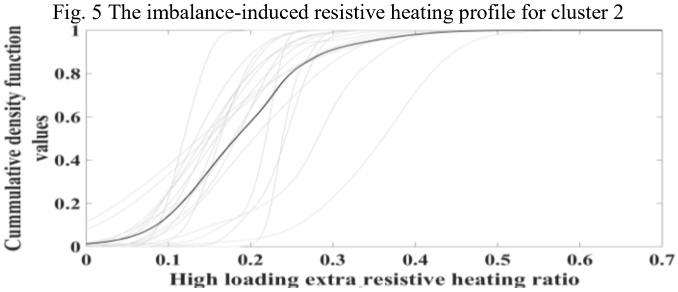

Fig. 6 The imbalance-induced resistive heating profile for cluster 3

For cluster 1, the average and maximum high loading extra resistive heating ratio achieve 3.4% and 15.3% respectively; for cluster 2 and clusters 3, the average and maximum high loading extra resistive heating ratio achieve 7.8%, 31.7% and 19.3 %, 50.4% respectively. In addition, cluster 1 accounts for 65% of LV transformers in the UK; cluster 2 and 3 accounts for 29% and 6%, respectively.

C. Discussion

With this research, the typical imbalance-induced resistive heating profiles are derived. It leverages only 800 LV networks to find a general picture of the imbalance-induced resistive heating profiles for over 900,000 LV networks in the UK. However, these results cannot be directly used in other countries. To apply this method in other countries, the selection of input data is a key criterion, i.e. it requires a collection of time-series phase current data for several LV networks. These LV networks should be representative, i.e. they should cover a good mixture of LV network's geographic scenarios (urban, suburban, and rural) and LV network's load scenarios (domestic, commercial, and industrial). The more representative of these LV networks, the more accurate typical imbalance-induced resistive heating profiles is.

Given the typical imbalance-induced resistive heating profiles, LV transformers' temperature increase can be identified. For the details of the temperature increase, other scenarios are considered: 1. ambient temperature of LV transformers; 2. ambient humidity of LV transformer; 3. heat dissipation method. The future work will consider these scenarios, and calculate the specific temperature increase, efficiency reduction and the risk of overloading.

IV. Conclusion

Given only 800 monitored LV transformer, this paper leverage a data-driven approach to find the general picture of imbalance-induced resistive heating profiles in the UK. Compared to analyze over 900,000 LV transformers, this approach is cost saving, i.e. this proposed method does not require any deployment of new monitoring devices.

The clustering results (evaluated by Davies–Bouldin index) shows that, for over 40% of the transformers, if the three phases are balanced with heavy loading scenarios, there is a reduction of up to 15%-50% of the resistive heating generation. In addition, these profiles are very valuable in the future work for analyzing the transformer operation status in details, e.g. extra temperature rise, efficiency reduction and risks of overloading.

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